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Improved Estimation of Sir in Mobile Cdma Systems by Integration of Artificial Neural Network and Time Series Technique

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Abstract: This study presents an integrated Artificial Neural Network (ANN) and time series framework to estimate and predict Signal to Interference Ratio (SIR) in Direct Sequence Code Division Multiple Access (DS/CDMA) systems. It is difficult to model uncertain behavior of SIR with only conventional ANN or time series and the integrated algorithm could be an ideal substitute for such cases. Artificial Neural Network (ANN) approach based on supervised multi layer perceptron (MLP) network are used in the proposed algorithm. All type of ANN-MLP are examined in present study. At last, Coefficient of Determination (R^2) is used for selecting preferred model from different constructed MLP-ANN. One of unique feature of the proposed algorithm is utilization of Autocorrelation Function (ACF) to define input variables whereas conventional methods which use trial and error method. This is the first study that integrates ANN and time series for improved estimation of SIR in mobile CDMA systems.

Key words: Artificial Neural Networks, Power Prediction, Mobile Communication Systems, Rayleigh Fading Signal, Time Series, DS/CDMA

INTRODUCTION

Closed-loop power control and feed back procedure is crucial in the uplink transmission (from mobile to base station) to control mobile's signal transmition power by sending power control commands from base station to either lower or higher transmitting power level for each user independently to keep the received power level from each mobile unit equal and constant in the average. The capacity and quality of service of CDMA systems greatly depends on the mobile power control function. While an open-loop power control can solve the near-far and shadowing problems Turin, (1984). the closed-loop power control can combat multi path fading (Viterbi *et al.,* 1993). The inherent problem in a closed-loop power control algorithm is feed back delay. In this situation the information of power control command is outdated and not reliable. We need to predict the value of signal strength or SIR at the time that the power control commands should actually take place (Sim *et al.,* 1999). The closed-loop power control with predictive SIR estimation is illustrated in Fig.1. The estimator in the base station can either estimate the received signal strength or the SIR. In addition power control based on SIR is more suitable than that based on signal strength because CDMA is interference limited (Ariyavisitakul and Chang, 1993). A hybrid and modified elmann neural networks and Heinonen-Neuvo prediction were proposed in (Gao *et al.,* 1997; 1996) to predict signal strength and they used Predictive Minimum Description Length (PMDL) method to find the optimal neural network. In this paper the structure of MLP predictor is first optimized off-line and the performance of all mentioned structures are evaluated in terms of bias and mean squared error (MSE) then use the optimal predictor with on-line learning and adaptation in the real situation.

In section 2 a Rayleigh fading channel simulator and SIR estimator technique are described. In section 3 we discuss the topology of feed forward neural network-based power prediction and the applied learning algorithm. The optimized neural predictor is found off-line and applied to predict SIR in a Rayleigh fading

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channel. An illustrative simulation is demonstrated in section 4. Finally we conclude this paper with a few remarks and discussion in section 5.

The Integrated Algorithm:

The algorithm is shown in Figure 1. This algorithm has the following general basic steps:

Simulate SIR firstly. Then the stationary assumption should be studied for current data. If the data are not covariance stationary, the most suitable preprocessing method should be selected and applied to the model.

Divide data into two sets, one for estimating the models called the train data set and the other one for evaluating the validity of the estimated model called test data set. Usually train data set contains 70 to 90 percent of all data and remaining data are used for test data set Al-Saba and El-Amin, (1999).

Input variables for ANN model can be selected using Autocorrelation Function (ACF). However, in most heuristic methods, selecting input variables is experimental or based on the trial and error method (Aznarte *et al.,* Zhang and Qi, 2005; Zhang and Hu, 1998; Nayak *et al.,* 2004; Karunasinghea and Liong, 2006; Tseng *et al.,* 2002; Oliveira and Meira, Niskaa *et al.,* 2004; Aznarte *et al.,*Gareta and Romeo, 2006; Jain and Kumar; Hwarng, 2001; Palmer *et al.,* 2006; Kim *et al.,* 2004; Al-Saba ans El-Amin, 1999; Zhang, 2001; Ghiassi *et al.,* 2005). As there is no specified proposed method for selecting input variables in ANN, ACF approach is proposed to select input variables.

Importance of this approach is understood when difficulty and careless of trial and error method are considered. Irregular input selection is cause of its lack of preciseness. Even if all the previous lag combinations are used, the trial and error method will be time-consuming. For example, if all the combinations are selected from the recent 30 lag, the number of combination will be:

$$\sum_{i=1}^{30} \binom{30}{i} = 2^{30} \tag{1}$$

While ACF approach introduces few combinations for model input in comparison with trial and error process

Use ANN method to estimate relation between input(s) and output(s). For this reason select architecture and training parameters. All networks used in this study have a single hidden layer because the single hidden layer network is found to be sufficient to model any function. To find the appropriate number of hidden nodes, following steps are performed for networks with one to q nodes in their hidden layer. When the value of q is optional and should be changed after the following next steps, the goal error has not been achieved.

- •Train the model using the training data (S). In this study Levenberg-Marquardt (LM) training algorithm is used.
- •Evaluate the model using the test data (Sc) and obtaining Coefficient of Determination (R^2).

Training the preferred ANN-MLP model that is determined in step 4 with all of SIR data and predict next period. The main elements of the proposed algorithm are described next.

Data Preprocessing:

In time series methods, creating a covariance stationary process is one of the basic assumptions. Also, using preprocessed data is more useful in most heuristic methods (Zhang, 2001) which requires the investigation of stationary assumption for the models. If the models are not covariance stationary, the most suitable preprocessed method should be defined and applied. In forecasting models, a preprocessing method should have the capability of transforming the preprocessed data in to its original scale (called post processing). Therefore, in time series forecasting method, appropriate preprocessing method should have two main properties. It should make the process stationary and must have the post processing capability. The most useful preprocessed methods are studied in the sections.

The First Difference Method:

The first step in the Box-Jenkins method is to transform the data so as to make it stationary. The difference method was proposed by Box-Jenkins *et al.,* (1994). Also Tseng et al. used this method in their article to estimation time series functions using heuristic approach (Tseng *et al.,* 2002). The following transformation should be applied for the method:

$$y_t = x_t - x_{t-1} \tag{1}$$

Artificial Neural Networks:

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. Although ANNs arose to model the brain, they have been applied when there is no theoretical evidence about the functional form. In this way, ANNs are data-based, not model-based. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true for ANNs as well. In general neural networks are simply mathematical techniques designed to accomplish a variety of tasks. Neural networks can be configured in various arrangements to perform a range of tasks including pattern recognition, data mining, classification, forecasting and process modeling. ANN has attributes that let it be perfect in some application where we need to learn a linear or nonlinear mapping. Some of these attributes are: learning ability, generalization, parallel processing and error endurance. These attributes cause that ANN becomes egregious in solving problem methods. ANNs are normally arranged in three layers of neurons, the so-called multilayer structures are input, hidden and output layers. Input layers which are neurons (also called nodes or processing units) introduce the model inputs. Hidden layers combine the inputs with weights that are adapted during the learning process. Output layer provides the estimations of the network.

Neural Network Modeling:

Usually train data set contains 70 to 90 percent of all data and remaining data are used for test data set. One of the problems that occur during neural network training is called overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations. Early stopping method is used for this problem. In this method the available data is divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error will normally decrease during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set will typically begin to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The test set error is not used during the training, but it is used to compare different models. It is also useful to plot the test set error during the training process. If the error in the test set reaches a minimum at a significantly different iteration number than the validation set error, this may indicate a poor division of the data set.

Case Studies:

The proposed algorithm is applied to SIR simulation data.

Rayleigh Fading Power Signal and SIR Estimator:

A. .Rayleigh Fading Channel Model:

One of the most commonly used methods to simulate a Rayleigh fading channel is described in (Jake, 1994) and is referred to as the Jake's method. A simplified channel simulator often assumes the superposition of plane waves, whose arrival angle are uniformly distributed and associated with different Doppler shifts, ranging from the minimum to the maximum specified by the mobile speed. The Jake's method assumes that the line-of-sight component is absent. When the number of paths is large enough, the base band signal received from a multipath fading channel is approximately a complex Gaussian process and it invoke central limit theorem. We can write the amplitude fluctuation of the base band signal as follows

$$\beta(t) = \frac{1}{\sqrt{L}}\Big\{ \sum_{l=1}^{L/2-1} [e^{j2\pi(f_D \cos\psi_l t - f_c\tau_l)} + e^{-j(2\pi(f_D \cos\psi_l t - f_c\tau_{-l})}] + e^{j2\pi(f_D t - f_c\tau_L)} + e^{-j2\pi(f_D t - f_c\tau_{-L})} \Big\}. \tag{1}$$

Here $\beta(t)$ is amplitude fluctuation, L is the number of paths and $\Psi_l(t)$ has a uniform distribution in $[0,2\pi]$ and $\tau_l << T_s$(T_s is the sample duration) in frequency- nonselective channel (Braun and Dersch, 1991). In this paper, we implement Rayleigh fading simulator using 34 paths (Jake, 1994). Here we consider a slow fading channel and the fading factor is constant within the symbol duration. The simulated Rayleigh fading channel with a maximum Doppler-spread f_D=50HZ during a 200 ms period is shown in Fig.2. The fading channel described in Fig.2. can be experienced by a mobile which is traveling at 30 km/h when the carrier frequency is f_C=1.8GHZ and transmitting data at a symbol rate of 60 ksps . We can see in Fig.2. that the received signal fluctuation frequently drops far below its average level due to Rayleigh fading.

B. SIR Estimation or Measurement:

The base station dispreads the received base band signal by the conjugate of the k^{th} user's spreading sequence and integrated over M chips. The j^{th} user's signal strength is attenuated by the factor $\frac{1}{M}$ (cross correlation between spreading sequences) after dispreading by the k^{th} user's spreading sequences (Viterbi, 1995; Peterson *et al.,* 1995; Proakis, 1995). The SIR of the k^{th} user during one symbol period can be expressed as follows

$$\gamma_k(n) = \frac{|A_k\beta_k(n)|^2}{\frac{1}{M}\sum_{j \neq k}|A_j\beta_j(n)|^2 + \sigma_k^2(n)} \qquad (2)$$

Here $\beta_k(n)$ is the fading channel coefficient and $\sigma_k(n)$ is the standard deviation of the Additive White Gaussian Noise AWGN experienced by the k^{th} user. The data symbols are oversampled to obtain a larger number of observations. To simulate the uplink fading channels, an independent and uncorrelated Rayleigh fading for each user $\beta_k(n), k$=1,2,...,12 is generated using the Jake's method as described.

The maximum Doppler spread is varied for each user from 17Hz to 170Hz to reflect different user's mobility.

$$f_D = 1.67 v_k \, Hz, \qquad v_k = 10.k \; km/h \qquad (3)$$

We add the AWGN with the variance $\sigma_n^2 = 7dB$ below the signal power level (SNR=7dB).

SIR measurement is performed in every time slot that corresponds to one power control interval T_P=0.667ms. The simulated fading envelope for a vehicle with speed of 10km/h and its corresponding SIR are shown in Fig.3. We used all data symbols in the time slot to estimate the SIR. The chip rate is assumed R_c=3.84 $Mcps$ as given in the 3G specification for uplink data channel. Therefore, 40 binary symbols per time slot are available for the SIR estimation.

It can be seen from Figure 4 that simulated data has a trend. As removing the trend is needed for more precise estimation in ANN modeling, the first difference method is applied. It can be seen in Figure 5 that the first difference method is the most likely candidate to have covariance stationary process.

test data is shown in Figure 5. Comparing the Figure 5 shows that test data is suitable because the various range of simulated data is considered in test data.

For ANN-MLP models, ACF approach is used to select input variables. According to Figure 6, SIR is the function of SIR value in the 1th , 3rd, 6th lags in preprocessed data.

Table shows the value of R2 for each constructed ANN. It seems the 8th model (it has 8 neurons in a single hidden layer) has the highest R2 and consequently is chosen as the preferred model. In Figure, the ANN architecture for the preferred network (8th model) is shown. Figure 7 present the MLP-LM performance of each model.

To enhancing efficiency of preferred ANN, the preferred ANN is trained with all of simulated data. Figure 8 shows the SIR trend for next 2 periods.

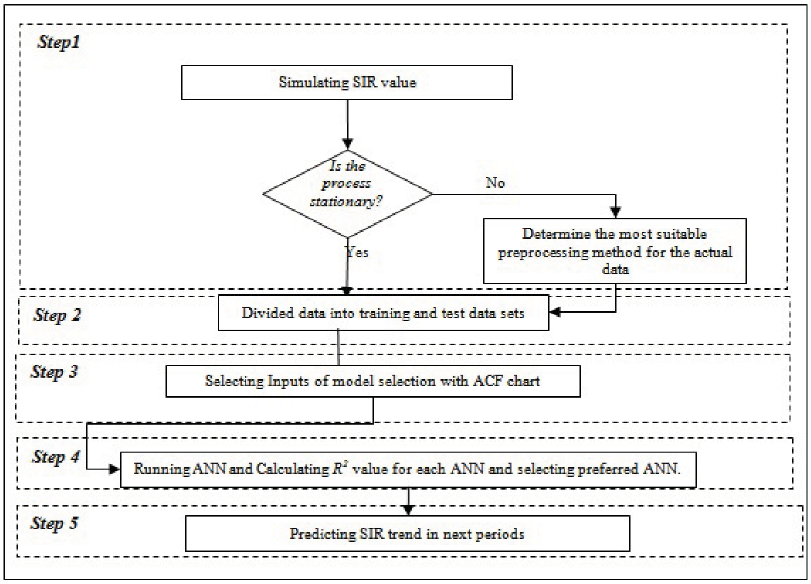

Fig. 1a: The integrated algorithm

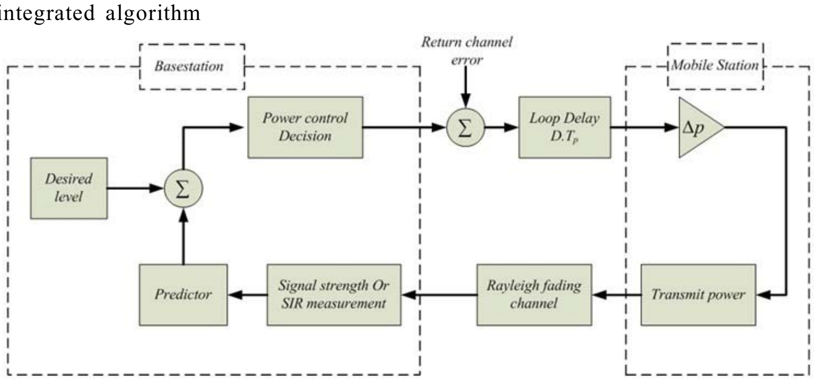

Fig. 1b: Closed-loop power control model

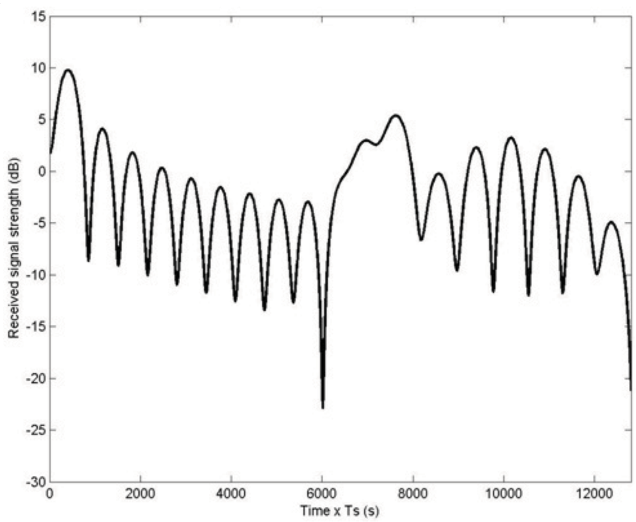

Fig.2.simulated Rayleigh fading ($f_D = 50Hz$, $T_s = 15.625\mu s$)

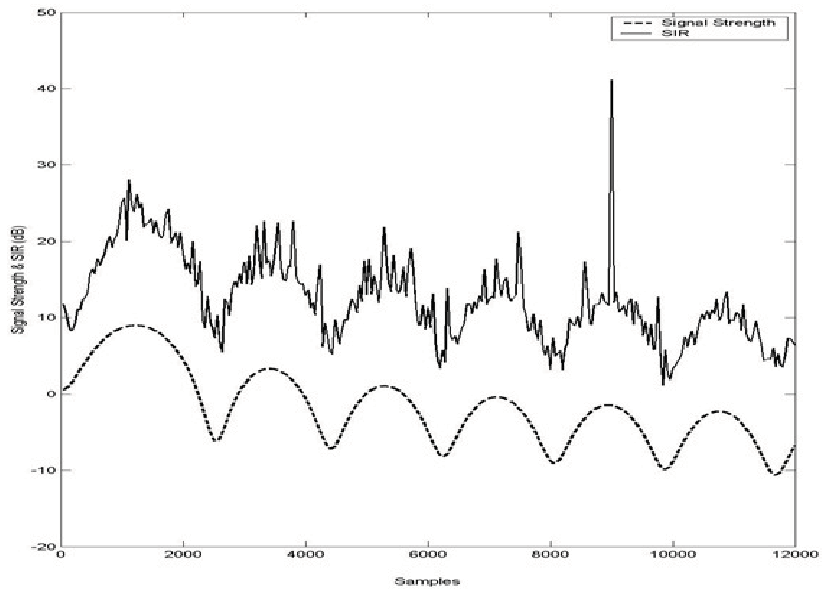

Fig. 3: SIR in Rayleigh fading $f_D = 17\,Hz$ with K=12)

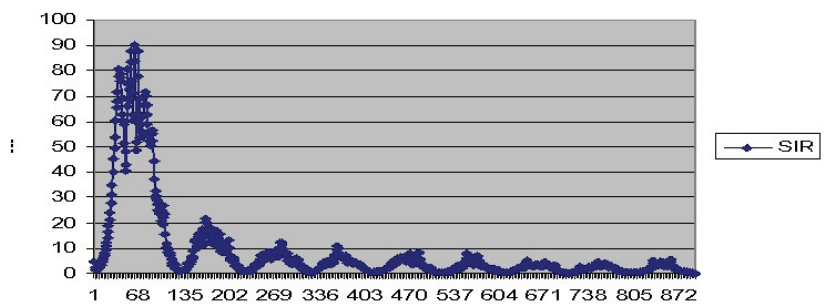

Fig. 4: SIR simulated data

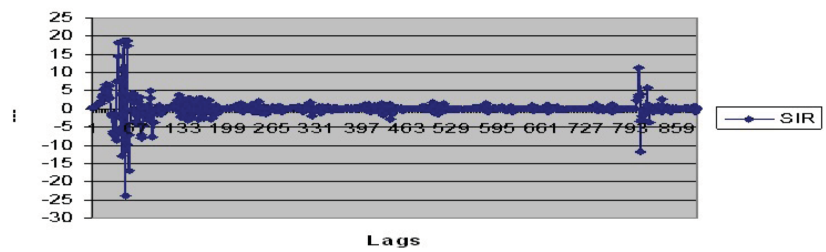

Fig. 5a: SIR Preprocessed data

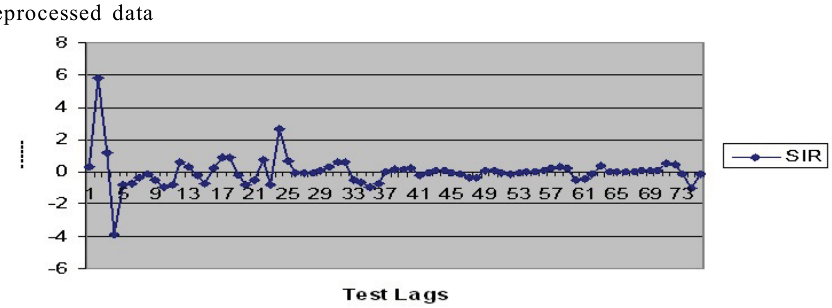

Fig. 5b: SIR simulated data (test section)

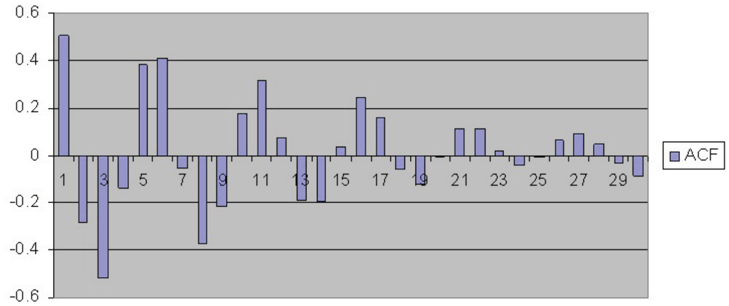

Fig. 6: ACF chart for SIR data

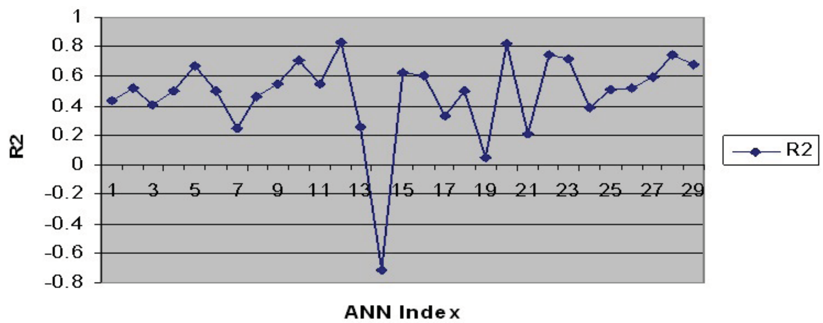

Fig. 7: R2 value for each constructed ANN

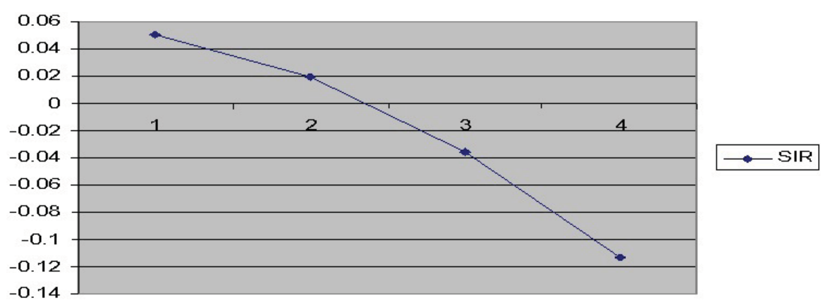

Fig. 8: SIR prediction with proposed algorithm

Conclusion:

We presented a MLP neural network-based single-step ahead SIR prediction scheme for reverse link power control in DS/CDMA systems. The neural predictor was optimized *off-line* using the MMSE method. Simulation results show that the optimized MLP neural network structure is capable of identifying the time-varying inverse dynamics of the multipath fading channel .To have the best prediction performance for on-line prediction the sampling rate should resemble the adaptation speed. Since the required sampling rate is only 1.5 KHz, so custom VLSI and DSP processors have the potential of matching training signal. Further investigation are being made to compare the response of optimized MLP with others neural network predictors in different vehicle’s speed. This is the first study that integrates ANN and time series for improved estimation of SIR in mobile CDMA systems.

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